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Modeling Coordinated Multiple Views of Heterogeneous Data Cubes for Urban Visual Analytics

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Modeling Coordinated Multiple Views of Heterogeneous Data Cubes for Urban Visual Analytics

With the explosion of digital data the need for advanced visual analytics, such as coordinated multiple views (CMV), is rapidly increasing. CMV enable users to discover patterns and examine relationships across multiple visualizations of one or multiple datasets. CMV have been implemented in a web-based environment known as the Australia Urban Research Infrastructure Network (AURIN) portal, a platform developed to support the visual exploration of urban datasets from distributed, heterogeneous sources in Australia. Specifically, the paper responds to the challenges in dealing with complexity and multidimensionality of datasets used in CMV. We rely on the concept of multidimensional data cubes as the theoretical frame for coordination across data cubes that underlie multiple visualizations. Using the concept of data cubes and hierarchical dimensions, we introduce strategies to automatically build render groups. This provides an implicit coordination based on cube structures and a framework to establish links between a dataset with its aggregates in one-to-many fashion. The CMV approach is demonstrated using aggregate-level data, which is provided through federated data services from across Australia. The paper discusses the issues around our CMV implementation and concludes by reflecting on the challenges in supporting spatio-temporal urban data exploration.

Keywords: visual analytics, spatial-temporal data, urban big data, brushing, linking.

Subject classification codes: include these here if the journal requires them

Introduction

As more people move into cities, there is an increasing need to understand the dynamics and behaviour of people and their relationship with the built environment to assist in planning for sustainable urban futures. With the recent emergence of big data, open government data, and crowd sourced data there is a need to provide access to visual analytical tools to support the exploration of such a rich tapestry of data. Urban researcher, policy and decision makers need approaches that can let them visually mine this rich data for better understanding the form and function of cities.

The Australia Urban Research Infrastructure Network (AURIN) is one such big data smart city initiative aimed at facilitating the access to, and analysis of data of relevance to urban researchers, policy and decision-makers across the country. AURIN is building a fully Web-based environment that enables the discovery and acquisition of diverse, spatially-referenced data (such as demographic datasets, public health datasets, GIS layers, and many other socio-economic datasets), and their interactive visualization and exploration in a rich user environment (Sinnott et al., 2012). The users interact with the environment through a shop-explore-analyse-create-collaborate cycle around research data (Tomko et al., 2012). The environment provides the researchers with a confirmatory data analysis capability, based on a workflow environment, and exploratory data analysis through various visual functionalities: 2D map, data grid, statistical charts, and 3D space-time cube (Pettit et al., 2012).

A fundamental property of AURIN is that all data are directly sourced, on-demand from autonomous, heterogeneous, federated data providers through targeted data services. In this context, facilitating the visual exploration of the patterns contained in and across disparate datasets in the context of the Digital Earth vision (Craglia et al., 2012) is a challenge that motivates this paper. Specifically, we are interested in how Coordinated Multiple Views (CMV) can be designed and implemented to support more integrative and exploratory analysis of loosely-coupled datasets, which may have very diverse and idiosyncratic structures.

CMV, or MLV (Multiple Linked Views) in some papers (Erbacher & Frincke, 2007; Jern, Johansson, Johansson, & Franzen, 2007; Roberts, 2004), provides an exploratory visualization (EV) environment, “where each of the views are linked together such that any user manipulation in one view is automatically coordinated to that of any other” to promote “insight through interaction” (Roberts, 2008). In this interactive visualization construct, two or more data views of identical or related datasets are made interdependent in order to enhance the data exploration and information seeking behavior of the user (Buja, Cook, & Swayne, 1996; Buja, McDonald, Michalak, & Stuetzle, 1991). Multiplicity of views has been claimed to decrease clustering, extend the analysis scope, contrast multiple facets of data, facilitate data comparison, enhance multivariate relationship, and avoid context switching via simultaneous display, which in turn increases users’ performance and satisfaction, especially when completing difficult tasks (Boukhelifa, Roberts, & Rodgers, 2003; Butkiewicz, Dou, Wartell, Ribarsky, & Chang, 2008; North & Shneiderman, 2000b; Pillat & Freitas, 2006).

Coordination, or view linking, can take many forms (Boukhelifa et al., 2003; Pillat & Freitas, 2006; Wang Baldonado, Woodruff, & Kuchinsky, 2000). Coordinated views may be simply displayed as small multiples, and optionally linked by graphical objects

(e.g. lines (Steinberger, Waldner, Streit, Lex, & Schmalstieg, 2011)). Coordination can also take interactive forms such as “linking” (Buja et al., 1991), including brushing and focusing, and “navigational slaving” (North & Shneiderman, 2000a). These are practically implemented as synchronization of selection, highlighting, filtering, scrolling, and zooming across views (and their preceding production steps, including data processing (Boukhelifa et al., 2003)).

CMV have been supported by various visualisation tools: xmdvtool (Martin & Ward, 1995; Ward, 1994), IVEE (Ahlberg & Wistrand, 1995), IRIS Explorer (Foulser, 1995), Spotfire (Ahlberg, 1996), cdv (Dykes, 1997), Descartes (Andrienko, G. L. & Andrienko, 1999), and Amira (Stalling, Westerhoff, & Hege, 2005). They have also been widely used in a number of application contexts such as biology (Graham & Kennedy, 2001; Guo, 2003), physics (Doleisch, 2007) and finance (Chang et al., 2007). In particular, CMV are highly relevant to geospatial application, for example: CommonGIS (Andrienko, G. L. & Andrienko, 1999), GeoVISTA studio (Takatsuka & Gahegan, 2002), Improvise (Weaver, 2004), Geoviz Toolkit (Hardisty & Robinson, 2011) and Weave (Baumann & Adviser-Grinstein, 2011). In the geospatial domain, CMV have been used in the visualization of both 2D spatial data (Anselin, Syabri, & Smirnov, 2002; Butkiewicz et al., 2008; Gatalisky, Andrienko, & Andrienko, 2004; Guo, Chen, MacEachren, & Liao, 2006) and 3D spatial data, such as in LinkWinds (Jacobson, Berkin, & Orton, 1994) and Visage (Roth et al., 1996).

While the research on CMV has been steadily maturing over the past twenty years, some researchers have argued that CMV is not a “solved problem”. Research opportunity still opens for exploring how to provide a CMV mechanism that is suited to real life problem and how CMV should be developed further as part of Visual Analytics (Andrienko, G. & Andrienko, 2007; Roberts, 2007). Broader overview about this subject and CMV research challenges are well-documented as reported in the literature, see for example: Andrienko and Andrienko (2007), Roberts (2007, 2008), and Scherr (2008).

A relevant issue to this paper, data processing and preparation is identified by Roberts (2007) as one of the fundamental challenges faced by CMV designers. This challenge is even more pronounced in the geospatial research area, as Roberts (2008) suggested: “the sheer size, complexity and diverse nature of geographical datasets definitely have consequences for exploratory analysis”. In their most recent paper on the visual analysis of multifaceted scientific data, Kehrer and Hauser (2013) emphasise the challenge of data heterogeneity, where “levels of data abstraction” and “fusion of heterogeneous data at feature/semantic level” are still open ended issues for CMV.

The issues of data abstraction and fusion of heterogeneous data are the issues this paper specifically addresses. The application circumstances of this paper, visual analytics of diverse federated datasets, represent a contemporary challenge for CMV. This is naturally coupled with the rise of eScience and Big Data research disciplines (Hey, Tansley, & Tolle, 2009). More recent works on CMV around heterogeneous data reflect such trend (Kehrer & Hauser, 2013; Kehrer, Muigg, Doleisch, & Hauser, 2011).

The aim of this research is to first to develop a model for coordination across views generated from heterogeneous datasets, viewed as multiple data cubes; second, to present a strategy to automatically linking views based on their underlying multidimensional cube properties, and thirdly, present pragmatic application of the

model and strategy. The concepts of data cubes, popular in the context Enterprise Information Technology and Business Intelligence (Gray et al., 1997; Kimball, 1998), could provide a coordination framework in the same way CMV have used relational database concept (North, Conklin, Indukuri, & Saini, 2002; North & Shneiderman, 2000b). This is the main contribution of this paper.

Related Work on CMV Modeling

Various modelling and architectural approaches have been presented to formally model coordination in linking multiple views (Roberts, 2008; Scherr, 2008): (i) constraint-based programming (McDonald, Stuetzle, & Buja, 1990); (ii) relational-schema approach (North & Shneiderman, 2000a); (iii) the module view controller (MVC) pattern (Pattison & Phillips, 2001); (iv) shared coordination objects that host visualization parameters (Boukhelifa & Rodgers, 2003); and (v) visual abstraction language based on shared object (Weaver, 2004).

These approaches are aimed at various abstraction levels and various aspects of coordination. For example, the work of Pattison and Phillips (2001) concerns implementation architecture of generic view coordination. They apply the Model-View-Controller (MVC) pattern to separate the specification and implementation of mapping between data model to view model.

The Snap-Together model (North et al., 2002; North & Shneiderman, 1999, 2000a, 2000b) takes a data-centric approach in dealing with coordination. This approach simplifies the way the users create custom coordination through relational schemata, which is based mainly on relational database concept (Codd, 1970). Users control coordination of views by specifying a relational join between dataset schemas. This enables “snapping of visualizations” through a mapping in the form:

$$(view_a, action_a, tuple_a) \leftrightarrow (view_b, action_b, tuple_b)$$

where $action_a$ and $action_b$ are actions to be coordinated and $tuple_a$ and $tuple_b$ are dataset instances (rows in relational tables) that contain unique identifiers, which in most cases are expected to be equal keys within primary-key or foreign-key joins (Scherr, 2008).

Boukhelifa et al. (2003) introduce a model that “handles coordination from a more general viewpoint and takes into consideration exploratory visualization needs for rich and varied user interactions.” The model is intended to address the coordination design issues without bias towards a particular data, navigation or communication paradigm. To achieve this, it presents a formal layered model grounded on a high-level conceptual view of visualisation, in which coordination could take place during any stage of visualization data flow: enhance, map, render, and transform (Chi, 2000; Haber & McNabb, 1990).

Weaver (2004) proposes a visual abstraction language and a coordination mechanism based on shared-objects, which is combined with indirect coordination through a query mechanism. Coordination is performed on controls (e.g. views and widgets), which are associated with one or more live properties. These properties can be bound to shared objects (or variables). Distinct variables can be indirectly coordinated through lexical

translation.

Coordination for Data Cubes

Traditionally, a multivariate dataset used in visualisations and visualisation research is typically described in a relational sense, a tabular dataset with n records (or rows) and p attributes (or columns), with the attributes being mostly cast as numerical values (even for categorical ones). This kind of dataset is often depicted as a collection of n points in a p -dimensional Euclidean space (McDonald et al., 1990).

Such conceptualization of data is grounded on the relational data model (Codd, 1970), which is a de-facto standard for many database implementation. In the more recent years, an alternative multi-dimensional conceptual model, data cube, is gaining traction particularly in the business and management areas to support Online Analytical Processing (OLAP) and Data Warehousing (Gray et al., 1997; Kimball, 1998). Before outlining the way views are coordinated by taking advantage of their underlying data cube structure, we present in more detail the concept of the data cube.

Data cubes

Data cubes provide an abstraction that specifically supports a mechanism to quickly deliver summarizations and aggregations of the underlying data at various levels (or more precisely dimensions). Broadly speaking, data cubes organize information into “dimensions” and “measures”, which roughly corresponds to the independent and dependent variables, respectively (Stolte, Tang, & Hanrahan, 2003). Conceptually, dimensions are represented as axis of a data cube and measures are contained within “points” or “cells” of the cube. Thus, a particular measure (typically numerical value) is referenced based on a combination of dimensional values. The term dimension here is different to the traditional notion of dimension as in multidimensional data in scientific discipline. Cube dimensions typically (but not always) capture the categories of categorical data (both ordinal and nominal).

As an example in the context of Australia using population census data, consider the population dataset over gender across different states, where the dimensions of interest include *GENDER*, *AREA* (e.g. state), and *TIME* (e.g. year). A measure of such dataset would be *TOTAL*, which refers to the total population according to the relevant values of dimensions (see **Figure 1**). Each row in the original cube C represents a tuple of the cube, a mapping between dimensions and measures.

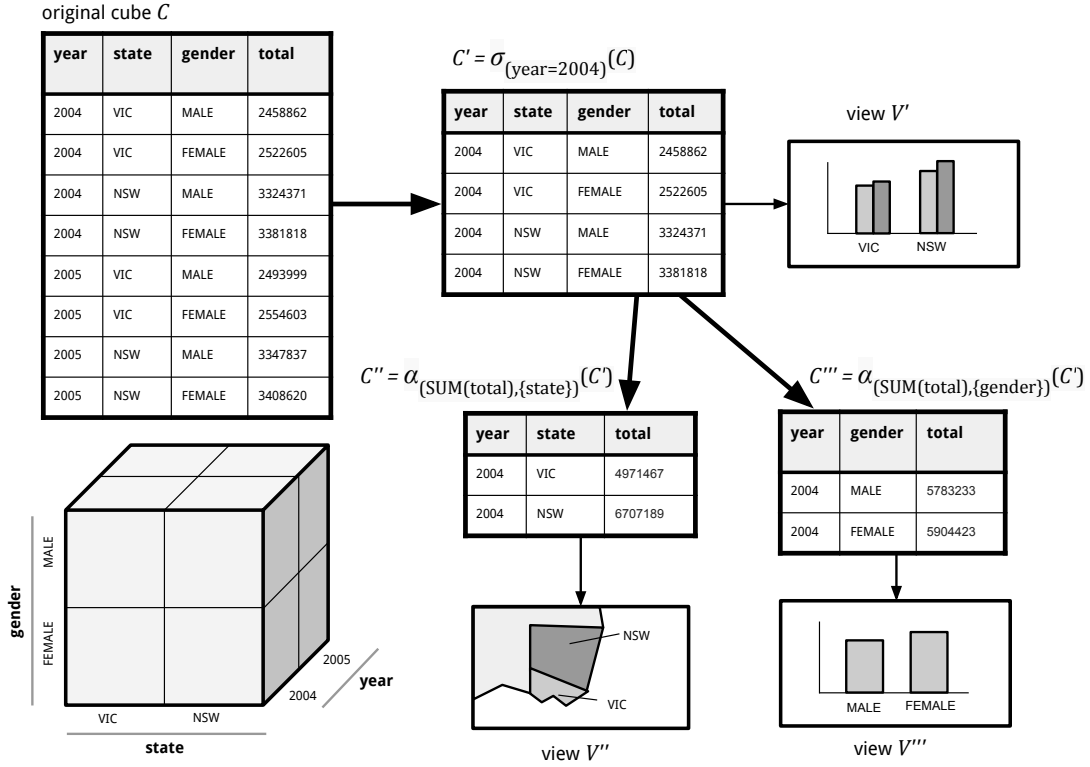


Figure 1. Population data cube based on Australian Census data with some operations performed on it. C is a cube with 3 dimensions (AREA, TIME, GENDER) represented in the attributes (*state*, *year*, *gender*) respectively; C' is restriction based on *year=2004* (slice operation); C'' is a SUM aggregate of C' for each *state* regardless of *gender*; and C''' is also a SUM aggregate of C' for *gender*.

Several papers have used the data cube as a reference model in their implementation of CMV (Guo et al., 2006; Jern et al., 2007), however they lack formalism in design of a cube multidimensional model. Similarly, Weaver (2010) presents a method for interactively expressing sequences of multidimensional set queries by cross-filtering nominal values of dimensions across pairs of views. Stolte et al. (2003) employ hierarchical attributes in a dimension of data cubes to support multiscaling. In building upon such research, this paper aims to explicitly focus on the use of data cubes in supporting CMV (in the spirit of Snap-Together's treatment of relational construct).

The structure of data cubes C can be formally defined as a 4-tuple:

$$\langle D, M, A, f \rangle$$

where D refers to a set of n dimensions d_i , M a set of k measures m_i , A a set of w attributes a_i , and f refers to a one-to-many mapping function $f: D \rightarrow A$ for which attribute sets across dimensions are pairwise disjoint, i.e. $\forall i, j, i \neq j, f(d_i) \cap f(d_j) = \emptyset$ (Datta & Thomas, 1999).

For the example above based on Australian census data extracted through the AURIN portal via the Australian Bureau of Statistics:

$$\begin{aligned} f(GENDER) &= \{gender\} \\ f(AREA) &= \{municipality, state\} \end{aligned}$$

$$f(TIME) = \{month, year\}$$

Note that attributes of a dimensions may form a hierarchical structure. TIME dimension, for example, can contain nested temporal scales $\{week, month, quarter, year\}$.

The actual instance of data cubes can be defined as a collection of cube tuples (similar to row in the relational sense), which are the results of a map g between Cartesian product of all domains of n dimensions D and k values of measures M ; so g is defined as $g: dom(D_1) \times \dots \times dom(D_n) \rightarrow (\mu_1, \dots, \mu_k)$.

The power of data cubes lies in the operations that can be performed on groups: slice, dice, aggregate, drill-down, roll-up, and cross-tab (Datta & Thomas, 1999; Gray et al., 1997). Slice and dice almost correspond to the relational algebra operator's selection and projection. They belong to *restriction* operator (σ), which restricts the values on one or more dimensions but does not change the structural properties of the cube (maintains $\langle D, M, A, f \rangle$). The *aggregation* operator (α) applies aggregation functions (e.g. SUM, AVERAGE, COUNT, MAX, MIN) on measures over one or more dimensions (more precisely grouping attributes). This operator produces a cube with a new $\langle D, M, A \rangle$. Aggregation facilitates *roll-up*, in which summarization is performed along one dimension adding a new aggregation level; *drill-down*, where summarized data is unpacked along a dimension to show more detail information; and *cross-tab* (or pivot) where symmetric aggregation is performed over n dimensions. These operators produce a new data cube, which may or may not maintain its original structural properties (for example of these operations, see **Figure 1**).

In general, aggregation is probably the most relevant in the context of visualisation. This operation produces a summary statistics that can be useful in supporting overview-and-detail views (North & Shneiderman, 2000a). Linking with data aggregates has been highlighted in the several CMV applications, either as aggregated spatial subspaces (Guo et al., 2006) or aggregated statistics (Chang et al., 2007; Hienert, Zapilko, Schaer, & Mathiak, 2011; Kehrer, Filzmoser, & Hauser, 2010).

Our example of population cube (**Figure 1**) illustrates opportunities to coordinate the original data cube with all of its aggregate cubes. The obvious use case of such coordination is to link the detailed view of the original dataset with the views that use the derived statistical aggregates (SUM, AVERAGE, COUNT). This overview-and-detail view represents a linkage between aggregates (data summary) and raw tuples (data details). Additionally, a cross-aggregate linkage may be established between two cubes if there is at least one common dimension between the cubes. This allows viewers to simultaneously inspect various levels of summaries.

Hierarchical dimension

Cube dimensioning is a powerful concept because it may be used to capture hierarchical structure, which provides more comprehensive aggregation levels. These hierarchical aggregation levels can form an abstraction for guiding the exploration of the data cube. This has been used in several CMV applications. Stolte et al. (2003) devised a method for independently zooming along one or more dimensions to visually explore data at different spatial levels (US states and counties). Graham and Kennedy (2001)

demonstrated hierarchical linking and focus using tree-structured data. These two examples show how coordinated displays, coupled with aggregation over hierarchical dimensions, can be useful in visual data navigation, particularly to support overview-and-detail views.

In the context of the AURIN portal, hierarchical structure of spatial dimension is a very important aspect in the management of a myriad of data products including the population census, which is critical for socio-economic profiling of human settlements . First, most of the datasets provided across the federated sources are aggregated at a particular spatial level (Delaney & Pettit, 2014). This level is typically an administrative division, like State and Local Government Areas (or LGA, which is roughly similar to US counties). Some datasets are provided only at a single level of geography, but many are available at various aggregation levels (thus, data cubes with hierarchical spatial dimensions are used behind the scene).

A few data contributors to the AURIN portal use their own defined spatial geography, for example, Functional Economic Region developed by University of Newcastle's Centre of Full Employment and Equity (Baum, Mitchell, & Han, 2008). However, most of the AURIN's urban datasets are aggregated at standardized levels specified by the Australian Bureau of Statistics (ABS) through its two regionalization standards: Australian Standard Geographical Classification (ASGC) and more recently the Australian Statistical Geography Standard (ASGS), which replaced ASGC during the course of AURIN portal development, hence both standards are supported.

In the context of AURIN, complication arose with the presence of multiple standards, thus different versions of spatial hierarchical dimensions (see **Figure 2**). AURIN merged this plethora of hierarchies and spatial levels in an encompassing hierarchy, which is represented as a common directed-acyclic-graph (DAG) G that specifies linkage and nesting relationship among various aggregation levels. Formally, a graph G is defined as a pair (V, E) , where V is a set of vertices that represents spatial levels; E is a set of edges between the vertices $E \subseteq \{(u, v) \mid u, v \in V \wedge u \neq v\}$, which represent parent-child or nested relationship between levels (see **Figure 2**).

All datasets provided through AURIN must use one of the compliant levels in their metadata description. In supporting CMV, this graph plays a critical part as the ontological foundation for coordination across views derived from various datasets produced at different levels.

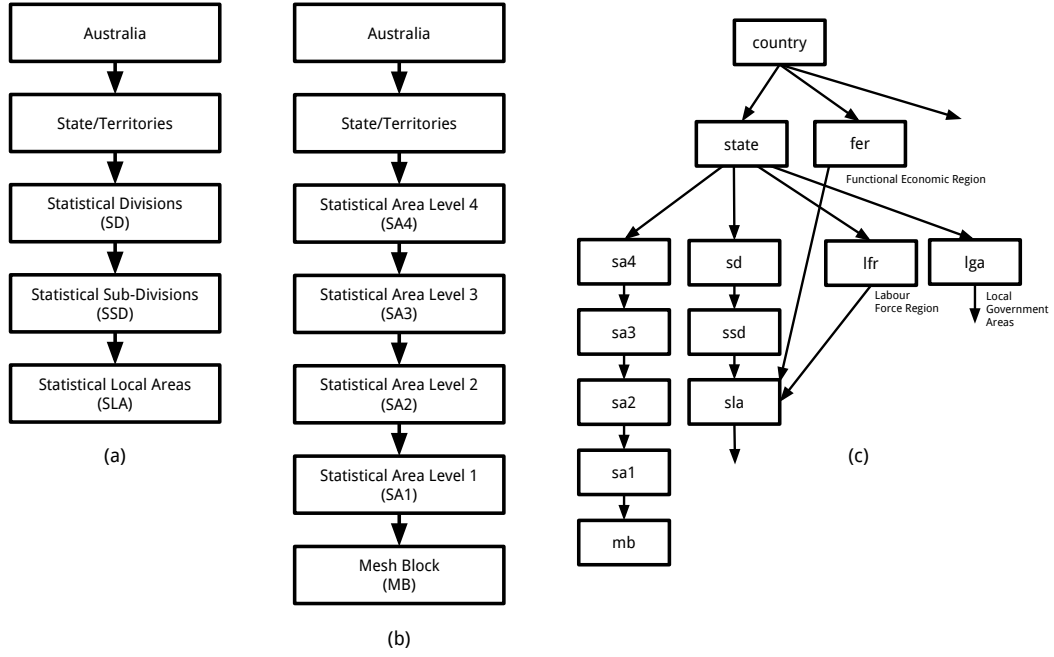


Figure 2. (a) Main component of Australian Standard Geographical Classification (ASGC); (b) Main component of Australian Statistical Geography Standard (ASGS); (c) a partial depiction of the combined DAG (directed-acyclic-graph) G that contains all valid aggregation levels and their inter-relationships.

With such a common hierarchy, it's possible to link a dataset to other datasets with different spatial level as long as their divisions (or administrative boundaries) respect each other. For example, a Statistical Area Level 1 (SA1) level dataset can be potentially coordinated with a SA2-level dataset. We can formally define the possibility to perform cross-levels linkage as follows:

$$S = s(v), v \in V$$

$$P = \rho(S)$$

where V is all possible levels of graph G (common hierarchy), $s(v)$ represents values of attribute from a set of divisions (or features) of level v (e.g. a is *state* or *LGA*), $\rho(S)$ is a set of partitions of S such that:

$$\bigcup_{p_i \in P} p_i = S \wedge p_i, p_j \in P, i \neq j \Rightarrow p_i \cap p_j = \emptyset$$

Let S_x and S_y be sets of subdivision x and y ($x = \textit{state}$ and $y = \textit{LGA}$), a relationship $L(x, y)$ between the two subdivisions can be established if there exist $h_{(x,y)}$ ($h: S_x \rightarrow P_{xy}$) and P_{xy} such that :

$$|S_x| = |P_{xy}|, s_i, s_j \in S_x, i \neq j \Rightarrow h(s_i) \neq h(s_j)$$

$$\bigcup_{s \in S_x} h(s) = \bigcup_{p \in P_{xy}} p = S_y$$

This means that subdivision x is the parent of subdivision y , or y is nested with x , or the boundaries of level x respect the boundaries of level y . This applies, for example, to the following pairs:

$$\begin{aligned} x &= \text{state}, y = \text{LGA} \\ x &= \text{SA4}, y = \text{SA3} \\ x &= \text{state}, y = \text{SA4} \end{aligned}$$

AURIN Datasets

Datasets provided through the AURIN portal can be viewed as a cube $C = \langle D, M, A, f \rangle$ with an attribute $a^* \in A$ as the dataset key containing identifiers from a particular spatial level $v^* \in V$ of graph G . Thus, an AURIN dataset must use a standardized aggregation level, which is the geographic aggregation of the dataset (whether the data relate to suburbs, statistical local areas SLA, or any other aggregated geographies contained within the ASGS or ASGC). These specifications, **primary key a^*** and **spatial level v^*** , are specified in the AURIN metadata registry. This registry also contains metadata for the dimensions, measures, and attributes (e.g. their user-friendly names, internal machine name, possible mapping for categorical values).

The next section shall outline how the concept of cube and hierarchical dimensions, in particular the spatial one, can be exploited to set up automatic coordination among views, which is a valuable visual analytical tool to support urban researchers.

Configuring Coordination

The coordination can be either automatically configured by the system (Mackinlay, 1986), or can be, with a certain limitation, defined by the user. Applications and tools such as LinkWinds (Jacobson et al., 1994), compound brushing (Chen, 2004), Snap-Together (North & Shneiderman, 2000a), Improvise (Weaver, 2004), InfoVis (Pillat & Freitas, 2006), and GeoViz toolkit (Hardisty & Robinson, 2011) allow users to compose their own CMV by selecting field-of-views, compositions, and linkages of views.

In this configuration, coordination may assume and establish commutative and transitive properties (North & Shneiderman, 1999) to expand the potential linkages. Coordinations are:

- (i) *commutative*: coordination between two views is bi-directional.

$$L_{AB} \leftrightarrow L_{BA}$$

- (ii) *transitive*: if view A is coordinated with view B and view B with view C, then A is also coordinated with C.

$$L_{AB} \wedge L_{BC} \rightarrow L_{AC}$$

The configuration technique in this paper builds upon the Snap-Together's approach, which relies on relational schemata to coordinate views (North & Shneiderman, 1999, 2000a, 2000b). In such an approach, configuring coordination means applying joins in the data schema. North et al. (2002) identify several types of join: *self join*, *single join*, *compound join*, and *multiple alternative joins*.

Self join coordinates two views that display the same relation. In this case, the coordination corresponds to the inherent association that exists between two visualizations derived from a single dataset. *Single join* can be established between two views whose underlying data relations have a direct join as specified in the data schema. In the relational sense, this join is realized through two primitive associations: (i) *one-to-one*, where primary-key to primary-key relationship is used, and (ii) *one-to-many*, where a primary-key to foreign-key relationship is used (North & Shneiderman, 2000a). The *compound join* is established through indirect association between two views via one or more intermediate relations in the data schema. This takes advantage of the *transitive* coordination properties along the indirect association path. Such a join enables more complex many-to-many associations. Lastly, in *multiple alternative joins*, two views may have multiple kinds of join associations, which require a selection or merging the join associations.

Coordination Model for Data Cubes

One important aspect of configuring coordination is to produce *render-groups* (Boukhelifa & Rodgers, 2003; Roberts, 1998), which are a set of associated views. As prior section has established, in most visualisation tools, these groups have to be defined explicitly by users. This means, explicit configuration of n views requires at most examination of 2^n possible combinations.

We take a more opportunistic approach in setting up this configuration. We feel that attempting to automatically establish linkage as much as possible will relieve the users from manually defining the linking either in the underlying data relations or in the views themselves. This is important when developing a user-friendly portal, which is designed for urban planners, geographers and urban designers to use.

Our approach follows Snap-Together model (North et al., 2002; North & Shneiderman, 1999, 2000a, 2000b) and takes a data-centric approach in dealing with coordination. To automatically establish render-groups across views, the approach examines the relationship or coordination between underlying data cubes on which the views are based. To do this, we consider three strategies (see **Figure 3**):

- Common data cubes. Several views or visualisations that use a common data cube belong to the same render group.
- Derived data cubes. Render groups can be established between a cube and its derivations, which could be generated through a generalised analytical functions (such as classifier, spatial analysis) or through more basic cube operators like *restriction* operator (σ), *aggregation* operator (α) and their combinations.

- Data cubes with universal common-dimensions. Two datasets from two separate federated sources can be linked together if they share a common dimension that is universally defined within the realm of all datasets (such as spatial dimension which is represented in AURIN's common aggregation hierarchy).

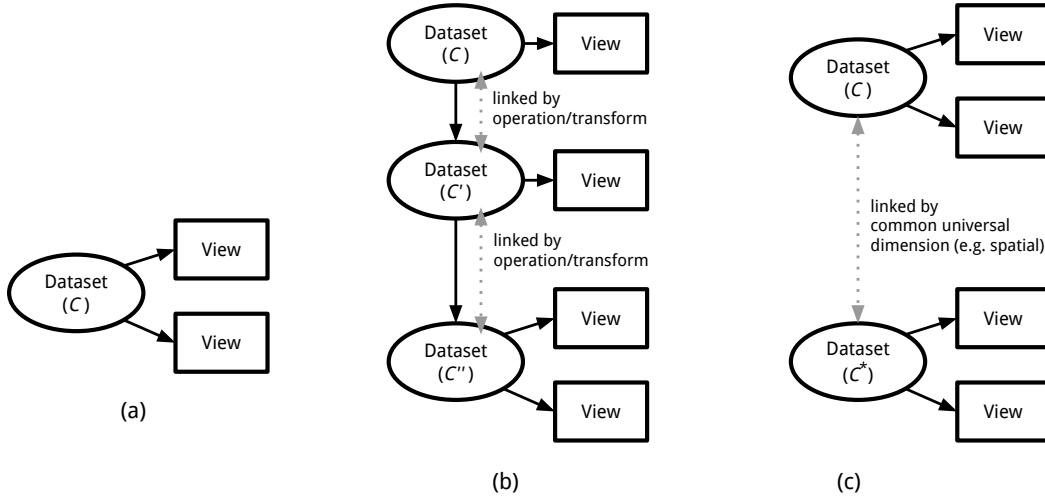


Figure 3. Automatic creation of render groups (a) Common data cubes. (b) Derived data cubes. (c) Cubes with universally common dimension.

These three strategies can be used to build dependencies graph in which potential coordination across views may be established based on the underlying datasets. In this graph, coordination follows the *commutative* and *transitive* properties.

The first strategy is similar to Snap-Together's self-join. All views that use the same dataset can be automatically coordinated. As such, the primary key a^* of the common dataset provides the link to any interactions across views. Thus, selection or brushing interaction will broadcast the value of the key to all other views that use the same dataset.

The second strategy utilises the data processing functionality of the AURIN portal, which provides features that can produce data aggregations and more complex data classification. In most situations, these resultant datasets maintain the structural properties of the source dataset. As such, all the datasets in the data analysis chain may be grouped in a single interdependent set. In the AURIN context, this data dependency is maintained and exploited for the coordination of CMV.

In this case, a data cube and its derivations that share at least a common attribute within their shared dimension can be automatically coordinated. As one use case, this provides an automatic linking between views (e.g. statistical aggregate charts) that summarize data (aggregation of a data cube) and those that show individual observations (data cube cells). Formally we can define this scenario as follows:

Let T be operation on a cube that produces another cube.

$$C = \langle D, M, A, f \rangle$$

$$C' = \langle D', M', A', f' \rangle = T(C)$$

Coordination $L_{CC'}$ between C and C' can be automatically assigned if:

$$\begin{aligned} D^* &= D \cap D' \neq \emptyset \\ A^* &= A \cap A' \neq \emptyset \\ \exists a_i, a_i &\in f(D^*) \cap f'(D^*), a_i \in A^* \end{aligned}$$

Using the example specified in **Figure 1**, the automatic coordination among views that rely on a cube and cubes produced through cube restriction and aggregation operations can be established as follows.

common dimensions $f(D^*) \cap f'(D^*)$	V	V'	V''	V'''
V		{state, gender}	{state}	{gender}
V'	{state, gender}		{state}	{gender}
V''	{state}	{state}		{}
V'''	{gender}	{gender}	{}	

Table 1. Coordination among views that uses a data cube and its derivatives (see Figure 1 for the description of the data cubes).

There are two ways by which coordination can be established for the actual data, at the tuple (row) level. If coordination is performed where data values matched for all common attributes (e.g. *state* and *gender*), i.e. linkage is determined via AND operator, then a conservative approach is taken.

$$\forall a_i, a_i \in A^*, t_C(a_i) = t_{C'}(a_i)$$

where:

$t_C(a)$ is tuple value of attribute a in cube C
 A^* is a set of attributes of the shared dimensions

If the relevant data cubes share the primary key a^* within the common dimensions, the coordination is bijective or one-to-one. Otherwise, one-to-many (surjective) mapping might be in place. Such a linking between detail datasets and summary datasets (for example, counts of a particular dimension produced through cube aggregation operator, or the histogram of Jenks classes) in a CMV display is highly desirable in an analytical interface. In Figure 1, one-to-many coordination can be established between, for example, V' and V''' based on *state* dimension, or V and V''' based on *gender* dimension.

If coordination is performed for at least one set of matched values on any attributes, then an aggressive approach is chosen. This is done via an OR operation on the values of common attributes. The consequences of this option is that linking try to find tuple matches as much as possible; as long as data instances share a common attribute valued, a link is establish. We call this *greedy* association.

$$\exists a_i, a_i \in A^*, t_C(a_i) = t_{C'}(a_i)$$

The third strategy assumes that it is natural that datasets for certain domain of

application share a common universal dimension. Formally, we say:

$$\begin{aligned} C &= \langle D, M, A, f \rangle \\ C' &= \langle D', M', A', f' \rangle \end{aligned}$$

Coordination $L_{CC'}$ between C and C' can be automatically assigned if:

$$D \cap D' \neq \emptyset$$

Several data cubes, which may be structurally different, may share a common universal dimension. So, in the case of AURIN, while datasets are sourced from different federated data providers, many share a common spatial dimension that is based on the same spatial structure. This structure is the common spatial aggregation hierarchy that is encapsulated as a directed acyclic graph G (see **Figure 2**). Each dataset shopped through AURIN should have LOCATION dimension, which is manifested as a primary key attribute. This attribute should contain standardized spatial identifier (like State identifier or LGA identifier), or at least can be translated to a standard identifier. In addition, to support the translation, a geospatial classification service is set up to store graph G and the partitions of various administration divisions in a spatial level in relation to other related levels (see **Figure 6**).

Coordination on the same spatial-level

The translation in the actual coordination is supported by geospatial classification service mentioned above, coupled with a metadata registry, which contains a necessary translation method for normalizing spatial identifiers contained in the dataset. These methods include no translation, regular expression, and lookup table (see **Figure 4**).

A method often used for the translation is regular expression. This is applied if and only if such a normalization is required (e.g., if a federated data provider has altered a primary key, for instance by prefixing an integer identifier by a string, such as "SLA" – short for Statistical Local Area, one of the administrative divisions /regionalizations of Australia). This regular expression is stored in the metadata registry together with aggregation level of the dataset (in this case, "SLA").

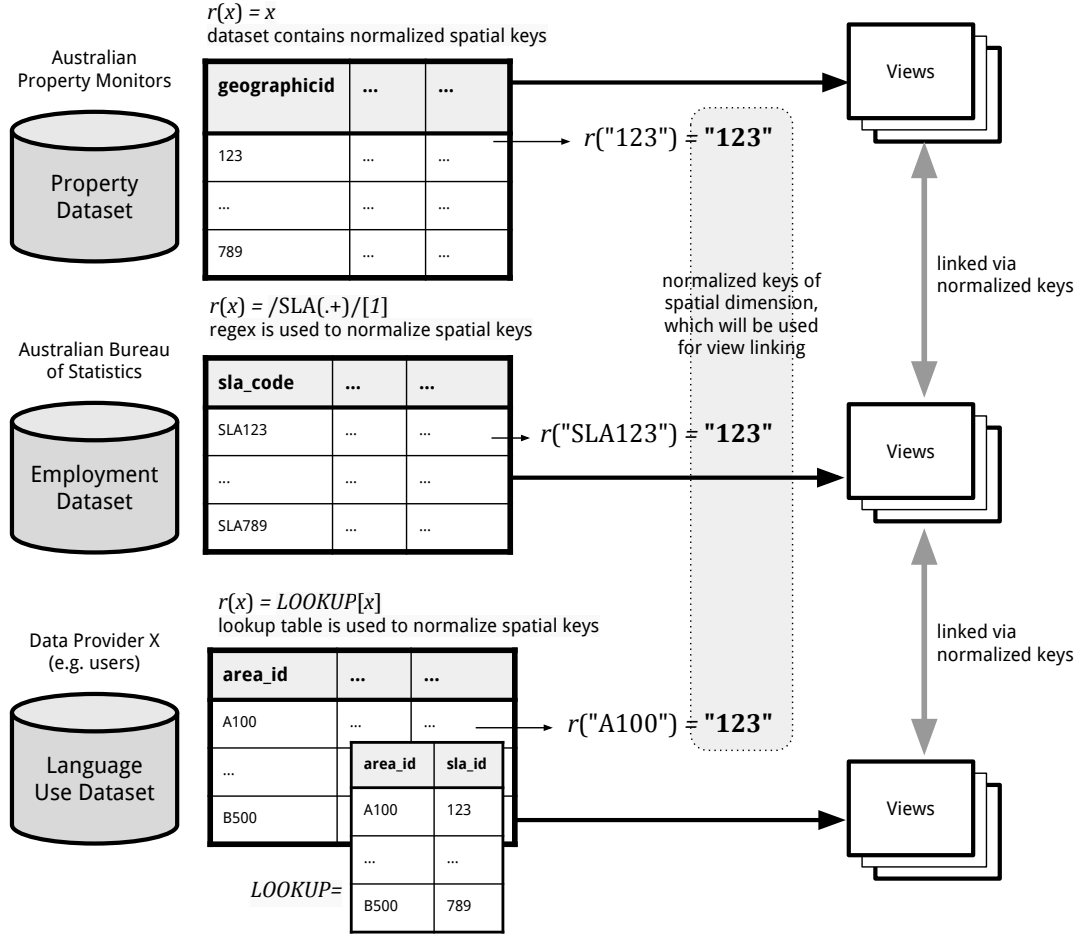


Figure 4. Coordinating views across multiple datasets by means of link normalization of SLA-level datasets. The tuples (or features, or rows) in each dataset can be linked based on their normalized values of the primary keys. Other than using AURIN-supplied datasets (e.g. from Australian Property Monitors and Australian Bureau of Statistics), user can also upload its own dataset. In this example, user can supply SLA-level language usage dataset.

Formally this linking can be described as follows:

$$C = \langle D, M, A, f \rangle$$

$$C' = \langle D', M', A', f' \rangle$$

Let C and C' be the cubes in the same render group, a^* and a^{**} are the primary keys (spatial identifier attribute) of the cubes respectively, $t(a)$ is a function that returns the value of attribute a of the tuples of the cube, r and r' are normalization functions for the attributes (stored in our metadata registry, or provided through geospatial classification service). Coordination can be established if:

$$r(t(a^*)) = r'(t(a^{**}))$$

These normalized spatial attributes, the primary keys of the dataset, relate to the unique identifiers of regions mapped in the various regionalizations (administrative divisions).

Figure 6. Example of one-to-many coordination across ABS SA3 datasets and SA4 datasets.

Coordination across different spatial-levels

As LOCATION is defined in the AURIN context based on a common spatial hierarchy G , it is also possible to establish linking across various spatial levels. This is done through geospatial classification service that provides translation and partition resolution support across multiple levels and regionalizations (see **Figure 7**). Such cross-level linkage allows one-to-many (surjective) mapping between parent and child spatial levels (see **Figure 6**).

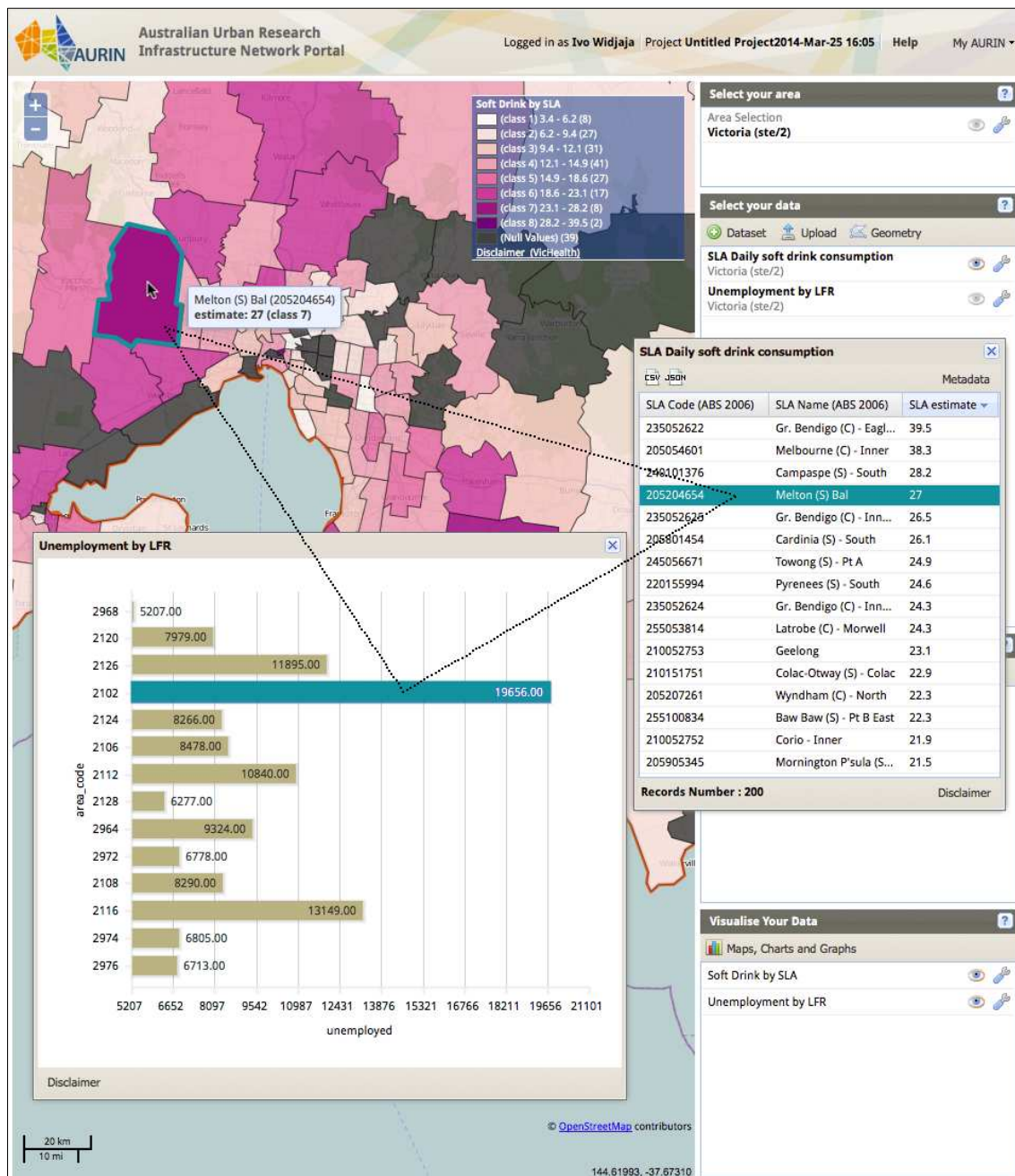


Figure 7. Example of coordination across different spatial levels between the ABS LFR (Labour Force Region) datasets and SLA datasets. One LFR comprises several SLAs. This is an example of one-to many relationship within a spatial dimension.

Conclusions and Future Research

In this paper, we have presented a model of coordination for multiple views of heterogeneous datasets. These datasets are conceptually seen as multidimensional data cubes, which own a set of structural properties: dimensions, measures, and attributes. The coordination is managed by examining the relationships across multiple independent and interdependent datasets based on these properties. This approach follows North et al.'s application of relational model on CMV (North et al., 2002; North & Shneiderman, 2000b) but by using multidimensional model.

We propose several strategies to automatically create render groups. Thus, linking across views can be established by exploiting the common dimensions of the cube and without requiring user to explicitly specify the linkage. These dimensions can be inherited from cube aggregation operation or some universal dimension such as standardized hierarchy of regionalization. View linkages can be established through normalized spatial identifiers, including across different spatial aggregation level.

We describe the use case of this approach in the AURIN portal, where CMV is applied in a federated data environment for enabling urban researchers, policy and decision-makers to explore big dataset for Australian cities. Some distinctive themes surfaced: the enablement of CMV in a distributed, heterogeneous database system requires more complex handling of hierarchical dimensionality, particularly the one that is shared such as spatial aggregation level. A metadata registry and a geospatial classification service are also needed as part of the coordination mechanism. We demonstrated this CMV approach across various forms of data views (table, charts, and choropleth maps).

Several issues in this approach need further investigation. The first one is performance. In our implementation, automatic linking across views based on common arbitrary dimensions currently relies on linear tuple scanning. This provides acceptable response time for a couple hundred tuples (or features), but a more sophisticated indexing process (such as on-demand indexing or automatic-caching of indexing) needs to be examined, particularly for point-based visualization. On-the-fly normalization and one-to-many matching can be computationally expensive. One possible solution to overcome this is the use of real-time indexing during the data prefetching or during the build of the views. This will be particularly useful for the interaction where response time is critical such as in brushing functionality. While some of these steps can be performed on the client side, it is also possible to offload the computationally heavy transformations (such as regular expression application) to a server-side process performed once, following the data discovery and acquisition process.

One-to-one linking using spatial dimension is handled reasonably well since the spatial identifiers are generally indexed primary keys. Linking across different spatial levels (such as between State and LGA) is supported by a geospatial classification service that relies on relational database. The potential benefit of using tree-based indexing needs to be examined further.

Another challenge in supporting this hierarchical dimension is the fact that two spatial levels might not be nested perfectly to each other. In this situation, how concordance tables may be used to allow coordination and the best form of coordination for this fuzzy linkage are two potential research opportunities.

The third issue is usability. This paper takes an automatic approach in configuring coordination, which is different to the typical CMV implementations. The comparison between such an implicit automatization and explicit configuration (such as the one used in Snap Together) requires further user study. This study should also investigate if linkage using shared dimension can be cognitively beneficial or confusing to the users, particularly when greedy association is used.

More broadly, future work in AURIN will bring in a significant number of urban settlement datasets at a range of aggregate and disaggregate scales. Other than cube-like datasets, AURIN will also provide relational-like datasets, non-aggregated data (street network, point-based dataset) and graph-based dataset. There is an on-going effort to investigate how our CMV approach can be further extended and improved to help users uncover relationships and pattern within this network of highly heterogeneous data.

Ultimately, our intention is to assist urban researchers, policy and decision-makers in being able to visually explore and interrogate this rich tapestry of data, which will go some way in representing the urban component of Virtual Australia (Thompson et al., 2008).

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